International Journal of Electronics Engineering (ISSN: 0973-7383)
Volume 11 • Issue 1 pp. 906-914 Jan 2019-June 2019 www.csjournals.com

Detection and Classification of MRI Brain tumor Image using Ensemble classifier

B.Lalitha[1],Dr. T.Ramashri[2]
[1] Research scholar, [2] Professor
Department of Electronics and communication Engineering, S.V.University, Tirupati

Abstract: Brain is the important part of our body. The change in the structure of brain from its normal is called brain tumor and causes abnormal growth of cell .The abnormality in cell growth sometimes leads to cancer and is to be diagnosed at earlier stages only. This paper presents a new supervised learning method for classification of brain tumor in MRI images. The proposed method provides accurate and fast way for diagnosing the brain tumor. This method utilizes feature vector based on the orientation analysis of gradient vector field, line strength measure, morphological transformation and Gabor filter responses.The feature vector contains information about healthy tissues of brain as well as tumor region.On the basis of these features classification of tumor is done as malignant or benign using an ensemble system of bagged and boosted decision trees. The experimental results shows that the proposed method performs moreefficiently and accurately. Prior to detection and classification of brain tumor a pre-processing of MRI image is done using Gaussian filter. The PSNR Value obtained after de-noising is better than mean, median filter.The segmentation technique used for extracting the tumor is edge based segmentation using gradient operator.

Keywords: Brain Tumor,MRI Image, Ensemble system, Bagged and decision trees

I. Introduction

Brain is the most important part of the body. The structure of brain is very complex and is protected by skull.This skull protects the brain from injuriesand provides information about health and disease of brain. sometimes there will be an abnormality in the growth of brain structure and its behaviour. These abnormal cell growth in brain is called as brain tumor. The cells which are tightly bound and supplies the brain in arteries require routine laboratory test and are inadequate to analyse functioning of brain. Doctors and researchers prefer two imaging modalities computed tomography and magnetic resonance imaging to study brain without any instrument introducing in the brain[1].Magnetic resonance imagine (MRI) is an advanced medical imaging technique uses magnetic fields, not x-rays, to produce detailed images of brain. Based on the type of tumor in the brain. There are different types of MRI. The clear Image of brain tumor is viewed using Intravenous (IV) gadolinium-enhanced MRI . Diffusion weighted imaging MRI technique provides the cellular structure present in the brain. perfusion imaging MRI Picturesabout blood reaching the tumor. A functional MRI (fMRI) provides information about tumor location of the brain that are responsible for muscle movement and speech[2].

There are many advantages of MRI Images over other imaging techniques .MRI brain images provide high contrast 3-D data between soft tissues of brain.MRI images are statistically simple with less number of classes and theoretically piecewise constant. A high contrast MRI image is produced by highlighting components present in the objects imaged with proper adjustments of radio-frequency(RF), relaxation timings and gradient pulses. On the other hand the piecewise-constant property is degraded considerably by electronic noise, the bias field (intensity in homogeneities in the RF field)and the partial-volume effect (multiple tissue class occupation which leads to overlap classes in intensity of histogram image.. Moreover, MR images are notalways high-contrast. Many -weighted and proton densityimages have low contrast between GM and WM. Therefore, itis important to take advantage of useful data while at the sametime overcoming potential difficulties. However, the amount of data produced by MRI Images is huge and become complex for manual analysis . hence an automatic Computer aided segmentation techniques are necessary for analysis/ interpretation and

segmentation of MRI Images in to grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF)

Our proposed ensemble system is robust technique and fully automatic .No prior knowledge of the image is required about its feature, contents, type and model. Proposed system is very accurate system for diagnosing the brain tumor. The paper is organized as follows: Literature review is represented in section 2. Details of the proposed method are described in section 3. Section 4 contains details of experimentation and results. Conclusion and future work is presented in section 5.

II.LITERATURE REVIEW

Fuzzy c-means (FCM) clustering [3] is an unsupervised system used to segment the MRI Images into two clusters based on membership functions.clusters are identified using intensity of pixel values. The main disadvantage of the "fuzzy"methods is that they seem to be unable to achieve good results unless complemented by other segmentation methods this tends to increase computational costs. Another shortcoming of fuzzy approaches is their sensitivity to noise

Saleck et al [4] introduced a new approach using FCM algorithm and GLCM Texture Features. FCM algorithm is used for extraction mass from region-of interest (ROI) with two clusters .The Gray Level Occurrence Matrix (GLCM) is used to get the texture features for the ROI Region.Based on the features obtained using GLCM tye accuracy of detecting tumor is better.The performance are evaluated for proposed method specificity, sensitivity and accuracy.

Rashid et al [5] investigated an SVM based tumor detection method tumor. A data set with abnormal MRI brain images were considered pre-processing of MRI images were done using anisotropic diffusion filter. For segmentation and extraction of tumor region an SVM classifier and morphological operations are used accuracy and execution time of this method is better.

Kanaly et al[6] proposed a semi-automatic approach in which the regions containing tumor are segmented manually . Again, the necessity of the user's manual interference may be impractical.

Stamatakis and Tyler[7] identify abnormalities in brain by statistical methods applied to T1-weighted images. every image is compared to a normal control group and the detected structure-differences between the image and the control group are taken as signs of abnormality. The drawback is that the segmentation results depend on the proper choice of the control group Besides, it is necessary to guarantee that the test data and the control group have been prepared using the same, parameters, scanner machine, coils, etc. This is not always possible.

Prastawa, Bullitt, Ho, and Gerig [8] The tumor-segmentation method proposed by is based on outlier detection using the T2 MR-image channel. The models for tumor segmentation are generated by means of intensity, and by the prior probabilities of tissues obtained from atlases. The shortcoming of this method is that on tumor regions get enhanced along with the tumor regions, and this reduces the performance of detection and segmentation. Moreover, the use of atlases requires accurate non-rigid registration of patient images to atlases where such a registration itself is difficult to obtain sizes also.

AmasyaliandErsoy [9] proposed ensemble classifier in order to improve the accuracy and execution time. Classification accuracy and execution time are two important parameters in the selection of classification algorithms. In these experiments, 12 different ensemble algorithms, and 11 single classifiers are compared according to their accuracies and train/test time over 36 datasets. The results show that Rotation Forest has the highest accuracy. However, when accuracy and execution time are considered together, Random Forest and Random Committees can be the best choices.

Sasikala et al. [10] discussed segmenting the Glioblastoma Multiform tumor from brain MR images. Theyused the special Gray level dependence (SGLDM) and wavelet transform methods to extract texture features andclassify the ROI from the brain tissues into normal and abnormal (tumor).

In [11], six features are computed by employing a multiscale analysis using a Gabor wavelet transformand Gaussian mixture model (GMM) Bayesian classifier. Ricci and Perfetti [12] used line operators and support vector machine (SVM) classification with three features per pixel. Lupascu et al. [13] introduced a feature-based Ada–Boost classifier for vessel segmentation which utilizes a 41-D feature vector at differentspatial scales for each pixel. In [14], a 7-D feature vector is computed by combination of moment-invariant and grey-level features and a five-layer feed-forward neural

network is used for classification. You et al. [15] computed the feature vector by using the steerable complex wavelet followed by calculating the line strength [12]

In this Paper a robust Decision tree based ensemble classifier is applied and it requires fewer features and is Simple in computation compared with than other methods .

III.Proposed Work

A)Pre-processing: This stage improves the quality of image and removes noise, Since brain MRI Images are more sensitive, the quality of these image should be maximum with minimum noise. Therefore a Gaussian filter is applied for MRI image data set before detection of tumor. Generally MRI Images are corrupted by Gaussian and Poisson noise[16].Most of noise detection algorithms assume additive white Gaussian noise. There are some algorithms designed for noise elimination, such as total variation, non-local means, bilateral filter with edge preserving. In this paper Gaussian filtering is applied to blur images and remove noise.The Gaussian filter is a non-uniform low pass filter.Low pass filtering removes high frequency components from an image.Gaussian filtering works by convolving the 2D Gaussian distribution function with the image.The coefficients of kernel diminish with increasing distance from the centre of kernel's. Central pixels have a higher weighting than those on the periphery. Larger values of σ produce a wider peak (greater blurring).

Kernel size must increase with increasing σ to maintain the Gaussian nature of the filter.With proper selection of kernel a 2-D Convolution is performed .the 2-D Convolution is obtained first by convolving with a 1-D Gaussian in the x direction, and then convolving with another 1-D Gaussian in the y direction. In 2-D, an isotropic (i.e. circularly symmetric) Gaussian has the form:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma}}$$

This distribution is shown in Figure 1.

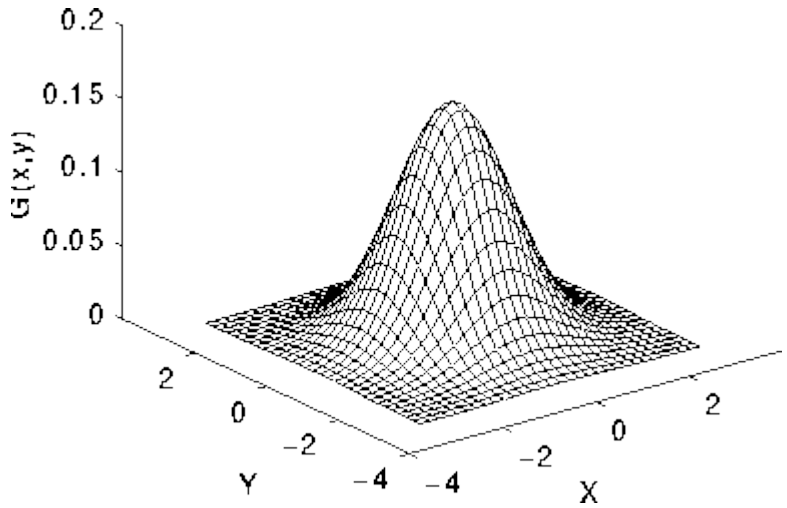


Figure 1 2-D Gaussian distribution with mean (0,0) and σ=1

B) Feature Vector:The feature vector s are extractedto each pixel for successful classification of tumor region. In this proposed work,9-D feature Vector are used that include the orientation analysis of gradient vector field(one feature) for removal of bright and dark lesions with enhancement, morphological transformation (one feature)for bright lesions removal with tumor enhancement, and a Gabor filter responses at multiple scales(four feature) for eliminating the dark lesions. One feature in the inverted green channel by considering the intensity of each pixel

i)Orientation Analysis of a Gradient Vector Field :The tumor represents the linear structures Hence,the Unit gradient vector of image are highly discontinuous.Hence the tumor regions are

localized by finding the discontinuities in the gradient orientation. The gradient vectors for the image f(x, y) are approximatedby the first-order derivative operators in the horizontal (kx) and vertical (ky) directions

$$gx(x, y) = I(x, y) * kx$$
$$gy(x, y) = I(x, y) * ky .$$

The gradient vectors gx (x, y)andgy (x, y) are normalized by dividing with their magnitude to compute the unit gradient vector ux (x, y) and uy (x, y):

$$ux(x, y) = gx(x, y)/\sqrt{g_x^2(x,y) + g_y^2(x,y)}$$

$$uy(x, y) = gy(x, y)/\sqrt{g_x^2(x,y) + g_y^2(x,y)}$$

The unit gradient vectors are assigned to zero if the gradient magnitude is too small (<3 out of 255). The discontinuities in gradient orientation are obtained by computing first derivatives of unit vectors

$$dxx(x, y) = ux(x, y) * kx$$
$$dxy(x, y) = ux(x, y) * ky$$
$$dyx(x, y) = uy(x, y) * kx \quad (3)$$
$$dyy(x, y) = uy(x, y) * ky .$$

The discontinuity magnitude in the gradient orientationD(x, y) is expressed in terms of the first derivatives of unitvectors as

$$D(x, y) = d2xx(x, y) + d2xy(x, y) + d2yx(x, y) + d2yy(x, y). \quad (4)$$

D(x, y) contains the GOA map of tumor region.The first-order derivative operator isemployed at multiple scales ($\sigma = \{\sqrt{2}, 2\sqrt{2}, 4\}$) to generatethe multiple GOA maps of Tumor of different widths.The final GOA map which also serves as one of the chosenfeature vectors is obtained by summing up the individual mapsproduced at multiple scales. The GOA maps containing the enhanced tumor are shown in Fig. 1. It is observed thatonly the curvilinear shaped blood vessels are enhanced despitethe presence of irregular shaped bright lesions in the first twoimages and the dark lesions in the third image.

ii) Morphological Transformation: The morphological opening using a linear structuring element oriented at a

particular angle will eradicate a tumor or part of it when the structuring element cannot be contained within the tumor. This happens when the tumor and the structuring element have orthogonal directions and the structuring element is longer than the tumor width.

$$Ith\theta = I - (I0Se\theta)$$
$$Isth = \sum_{\theta \epsilon A} Ith^{\theta}$$

The morphological top-hat transformation is shown in (5a) where "Iθth" is the top-hat transformed image, "I" is the image to be processed, "Se" is structuring elements for morphological opening, "o," and "θ" is the angular rotation of the structuring element. If the opening along a class of linear structuring elements is considered, a sum of top-hat along each direction will brighten the Tumor region regardless of their direction, provided that the length of the structuring elements is large enough to extract the tumor with largest diameter.Therefore, the chosen structuring element is 21 pixels long 1 pixel wide and is rotated at an angle spanning [0, π] in steps of π/8. Its size is approximately in the range of the diameter of the tumor region in the MRI image.

iii) Multiscale Gabor Filter: Gabor filter is widely used for multi scale and multi directional edge detection linear filter. Gabor filter can be fine tuned to particular directions, scales and frequencies and act as noise suppressor and low-level feature extractor. Gabor filter is a product of Gaussian kernel and a complexsinusoid and can be expressed as

$$g(x,y) = \exp\left\{-0.5\left(\frac{x'^2+\gamma y'^2}{2\sigma^2}\right)\right\}\left\{i\left(\frac{2\pi x+\varphi}{\lambda}\right)\right\}$$

where λ is the wavelength of the sinusoidal factor, θ is theorientation, ψ is the phase offset, σ is the scale of the Gaussianenvelope, γ is the spatial aspect ratio, $x' = x \cos\theta + y \sin\theta$,and $y' = -x \sin\theta + y \cos\theta$.The Gabor filter response to the inverted green channel of thecoloured MRI image is obtained by a 2-D convolution operatorand is computed in the frequency domain. The detailed procedurecan be seen in [11] and [16]. The maximum filter responseover the angle θ, spanning [0, π] in steps of π/18, is computedfor each pixel in the image at different scales ($\sigma = \{2, 3, 4, 5\}$).The maximum response across the orientation at a scale is takenasthe pixel feature vector. The feature space is normalized tozero mean and unit standard deviation by applying the normaltransformation.

iv) Line Strength Features :The concept of employing line operators for the detection of linear structures in medical images is introduced in [16] which is modified and extended in [12] to incorporate the morphological attributes of retinal blood vessels. The average grey level is measured alonglines of a particular length passing through the pixel under consideration at 12 different orientations spaced by 15◦ each. The line with the highest average grey value is marked. The line strength of a pixel is calculated by computing the difference in the average grey values of a square sub windowcentred at the target pixel with the average grey value of the marked line. The calculated line strength for each pixel is taken as the pixel featurevector.

2.Ensemble classifier: Ensemble classification is the process by which multiple classifiers are strategically generated and combined to solve a particular machine learning problem. Ensemble learning is primarily used to improve the classification or prediction performance of a model, or reduce the likelihoodof a poor or unfortunate selection. The ensemble methods combines multiple classifiers to obtain better predictive performance from many weak learners into one high quality ensemble predictor. We have used AdaBoostM1 and its variation Logit-Boost which are popular algorithms for binary classification.AdaboostM1 trains the learners in a sequential manner such that for every learner "k," the weighted classification error is computed as Ada-Boost is a boosting ensemble model and works especially well with the decision tree. Boosting model's key is learning from the previous mistakes, e.g. misclassification data points.

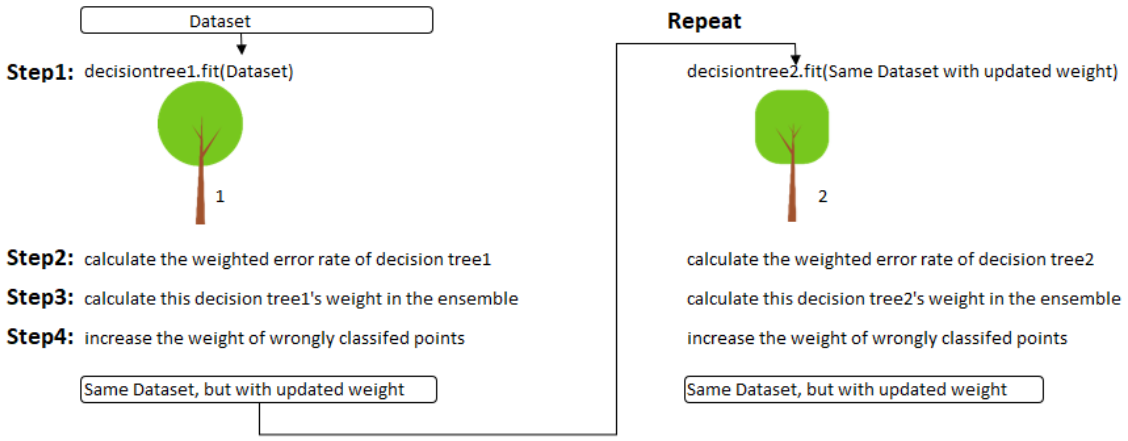


Figure 2 shows the Ada Boost Algorithm for classification of DICOM Data set

Processing step involved in classification

Step 1:Assign weights to each pixel in MRI Image.

Step2:Decision tree is trained with weights obtained.

Step 3:calculate the weighted error rate of decision tree.

$$Ek=\sum_{n=1}^{N} d_n{}^{k}\, I(y_n = h_k(x_n))$$

wherexn is the predictor value vector for n observations, yn isthe class label, $h_k$is the hypothesis, I is the indicator function and dknis the weight of observation at step k. The algorithmthen increases

weights for observations misclassified by learnerk and reduces weights for observations correctly classified bylearner k. The next learner k + 1 is then trained on the data withupdated weights dk+1n .The trained classifier then computes the prediction for newdata using

$$f(x)=\sum_{k=1}^{k} aa_k\, h_k(x)$$

such that $a_k = 0.5 \log \frac{1-\varepsilon_k}{\varepsilon_k}$ are the weights for weak hypothesesin the ensemble.

Step 4: Update weights of wrongly classified
The weight of each newdata point =Same,if the model got this data point correct
if the model got this data point wrong, the new weight of this point = old weight * np.exp(weight of this tree)
Step 5: Repeat Step 1(until the number of trees we set to train is reached)
Step 6: Make the final prediction

IV Results:

The proposed method has been tested on MRI Images consisting of Normal and tumor for various dataset available on website.In the proposed method 40 brain MRI Images are taken out of which 20 images are utilized for testing and 20 images in training phase.The experimental results shows that the proposed ensemble classifier have classified the MRI Brain Tumor Image Effectively than existing methods mentioned in literature survey. For each image in database a manually segmented image is considered as ground truth.Finally performance measure for classifier as tumor or non tumor isobtained based on four events two classifications and two misclassifications which are defined in Table I.

Table I Indicates the definition of performance measure

Measure	Description
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Accuracy	TP+TN/(TP+FN+TN+FP)
Precision	TP/(TP+FP)
Recall	FP/(FP+TP)

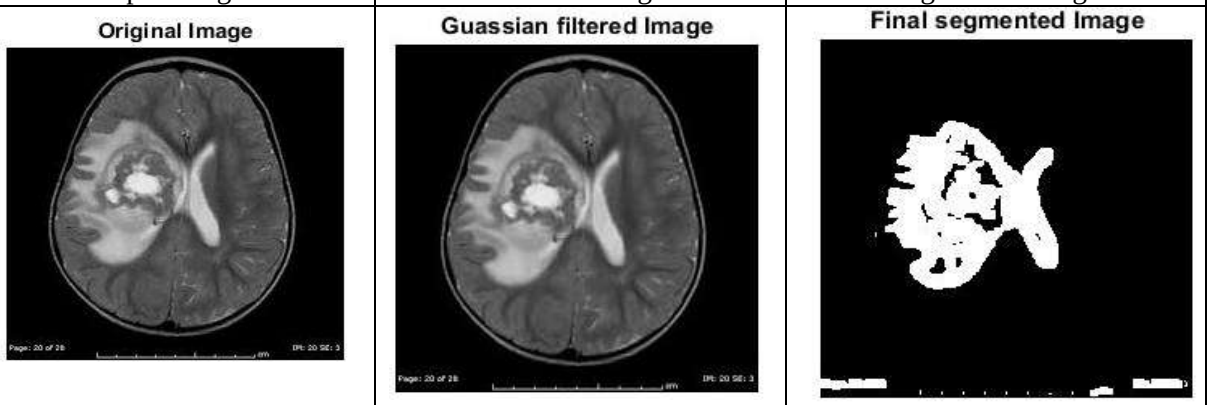
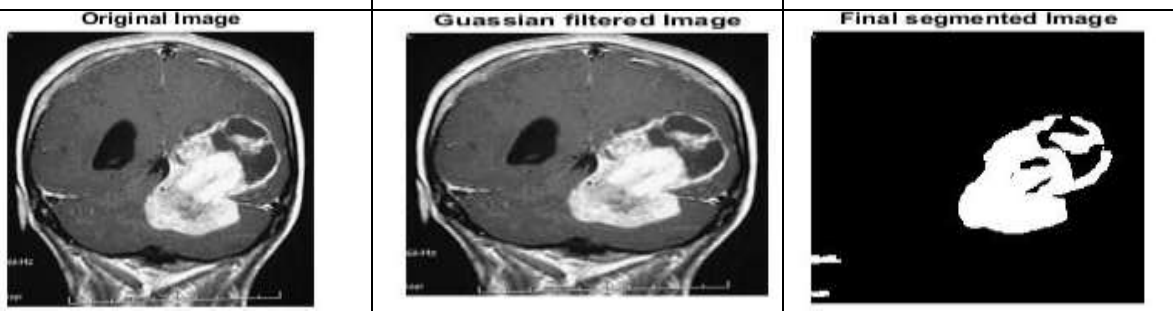
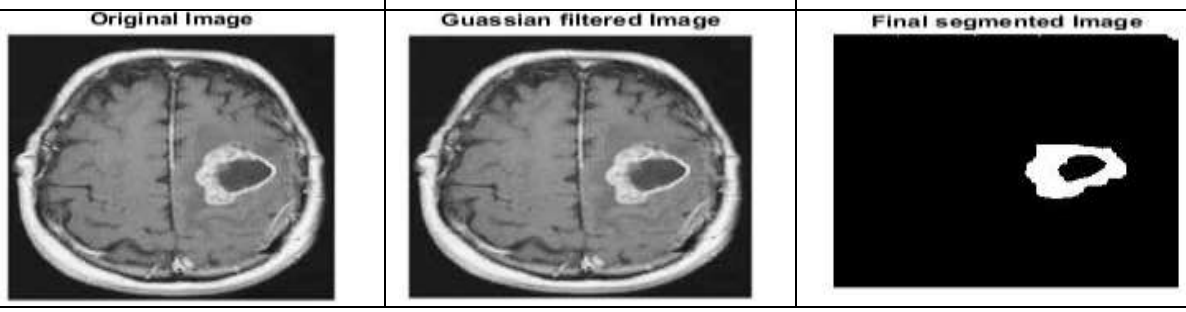
Accuracy:It is the ratio of correctly classified pixels to the total number of pixels in the image.
Sensitivity: it is the ability to detect tumor pixels in image.
Specificity: It is the ability of the algorithm to detect pixels of non-tumor region
Precision: It is the probability of identifying tumor pixels is a true positive.
Recall: It is the probability of identifying non tumor pixels is a false positive rate.

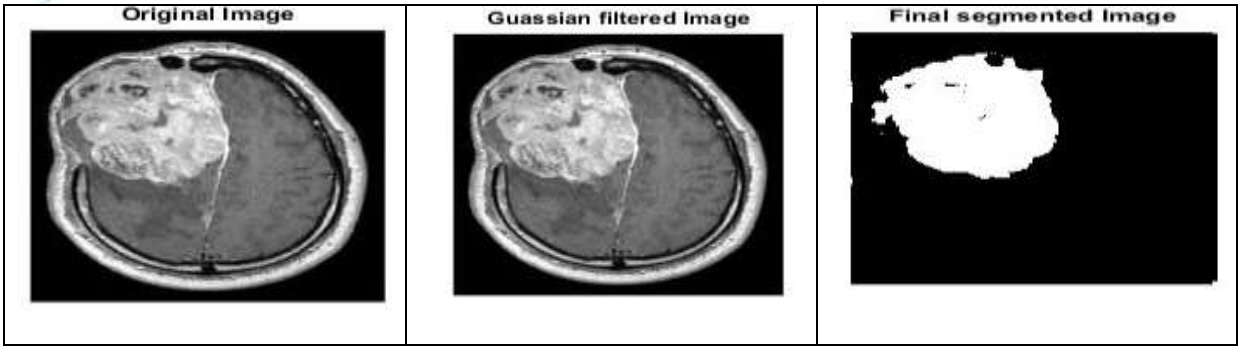
Table II Shows the results of performance measure

Input image	Accuracy (%)	Sensitivity	Specificity	Precision	Recall	PSNR Value using Guassian filter
Image-1	93.08	0.95	0.97	0.997	0.95	32.28
Image-2	98.12	0.98	0.98	0.998	0.98	32.33
Image-3	95.45	0.97	0.96	0.995	0.97	38.36
Image-4	97.69	0.99	0.99	0.999	0.98	32.25
Image-5	88.54	0.95	0.97	0.995	0.94	32.30

International Journal of Electronics Engineering (ISSN: 0973-7383)
Volume 11 • Issue 1 pp. 906-914 Jan 2019-June 2019 www.csjournals.com

The results shown in the above table II are compared with Parusaram Kumar and vijaykumar[17].the proposed ensemble classifier using Ada-boost gives better results with all performance measure the resultant tumor classified images for Dicom dataset is shown in the fig(3) below.

Input Image	Filtered image	Segmented image
		
		
		
		



Figure(3) shows the results of segmentation

V.Conclusions and future scope

In this paper an effective Brain tumor segmentation technique based on supervised classification using an ensemble classifier of Ada-Boost has presented. The proposed work utilized only 9-D feature vector mask obtained from gradient vector field; morphological transformation; line strength measures and Gabor filter response which gives information to successfully handle both normal and Abnormal tumor.The important feature of ensemble classifier is that the reliable estimates of the classification accuracy. The proposed method provides better accuracy,sensitivity and specificity than other existing methods. The proposed Ada-Boost ensemble classifier uses only nine features for pixel classification,thus utilizing less computational time. In future a new segmentation algorithm is preferred for efficient segmentation of tumor object.

REFERENCES

[1] Milan Sonka, Satish K. Tadikonda, Steve/M.Collins,Know1edge-BasedInterpretation of MR Brain Images , IEEE Transaction on Medical Imaging,. in section 5., 1996, pp. 443-452,Vol.15, No. 4.
[2]https://www.cancer.net/cancer-types/brain-tumor/diagnosis
[3]J. C. Bezdek, Pattern Recognition with Fuzzy/Objective FunctionAlgorithms New York: Plenum Press, 1981.
[4]Saleck, M. M., ElMoutaouakkil, A., &Mouçouf, M. (2017, May).Tumor Detection in mmography Images Using Fuzzy C-means and GLCM Texture Features.In Computer Graphics, Imaging and Visualization,).IEEE.2017 (pp. 122-125) 14th International Conference .
[5]Rashid, M. H. O., Mamun, M. A., Uddin, M. P. (2018, February)&M. A., Hossain,.Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images. International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2) (pp. 1-4). IEEE In 2018 .
[6]Kanaly, C. W. , Ding, D. , Mehta, A. I. , Waller, A. F. , Desjardins, A. , Samp- son, J. H. (2011),Crocker. I. A novel method for volumetric MRI response assessment of enhancing brain tumors. PloS One, 6 , e16031 .
[7]Stamatakis, E. A. ,& Tyler, L. K. Identifying lesions on structural brain im- ages–validation of the method and application to neuropsychological patients. Brain and Language, 94 , 167–177, (2005). .
[8]Prastawa, M. ,Bullitt, E. , Ho, S. , &Gerig, G. (2004). A brain tumor segmentation framework based on outlier detection. Medical image analysis, 8 , 275–283 .
[9]Amasyali, M. F., &Ersoy, O. K. (2011, June).Comparison of single and ensemble classifiers in terms of accuracy and execution time.In Innovations in Intelligent Systems and Applications (INISTA), 2011 International Symposium on (pp. 470-474).IEEE.

[10]Sasikala, M., N. Kumaravel and L. Subhashini, 2006. Automatic tumor segmentation using optimal texture features. Proceedings of the IET 3rd International Conference on Advances in Medical, Signal and Information Processing, July 17-19, 2006, Glasgow, UK.,pp: 1-4.

[11] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree,"Retinal vessel segmentation using the 2-D Gabor wavelet and supervisedclassification," IEEE Trans.Med. Imaging, vol. 25, no. 9, pp. 1214–1222,Sep. 2006.

[12] E. Ricci and R. Perfetti, "Retinal blood vessel segmentation using lineoperators and support vector classification," IEEE Trans. Med. Imaging,vol. 26, no. 10, pp. 1357–1365, Oct. 2007.

[13] C. A. Lupascu, D. Tegolo, and E. Trucco, "FABC: Retinal vessel segmentationusing adaboost,"., vol. 14, no. 5,pp. 1267–1274, Sep. 2010, IEEE Trans. Inf. Technol. Biomed.

[14] D. Mar´ın, J. M. BravoA. Aquino, andM. E. Geg´undez-Arias, ,, "A newsupervised method for blood vessel segmentation in retinal images byusing gray-level and moment invariants-based features," IEEE Trans.Med. Imaging, vol. 30, no. 1, Jan. 2011,pp. 146–158.

[15] X. You, Q. Peng, Y. Yuan, Y. Cheung, and J. Lei, "Segmentation of retinalblood vessels using the radial projection and semi-supervised approach,"Pattern Recogn., vol. 44, pp. 2314–2324, 2011

[16]I, Sanches, JRodrigues, Dias J. Denoising of medical images corrupted by poisson noise. In: Image processing, ICIP 2008. 1756–9,15th IEEE international conference on; 2008.p..

[17] Parasuraman Kumar, B. VijayKumar "Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier"ISSN: 2277-3878, Volume-8, Issue-1S4, June 2019.International Journal of Recent Technology and Engineering (IJRTE)